Assessment of river basin habitat quality and its relationship with disturbance factors: A case study of the Tarim River Basin in Northwest China

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Abstract: The status of regional biodiversity is determined by habitat quality. The effective assessment of habitat quality can help balance the relationship between economic development and biodiversity conservation. Therefore, this study used the InVEST model to conduct a dynamic evaluation of the spatial and temporal changes in habitat quality of the Tarim River Basin in southern Xinjiang Uygur Autonomous Region of China by calculating the degradation degree levels for habitat types that were caused by threat factors from 1990 to 2018 (represented by four periods of 1990, 2000, 2010 and 2018). Specifically, we used spatial autocorrelation analysis and Getis-Ord G_i^* analysis to divide the study area into three heterogeneous units in terms of habitat quality: cold spot areas, hot spot areas and random areas. Hemeroby index, population density, gross domestic product (GDP), altitude and distance from water source (DWS) were then chosen as the main disturbance factors. Linear correlation and spatial regression models were subsequently used to analyze the influences of disturbance factors on habitat quality. The results demonstrated that the overall level of habitat quality in the TRB was poor, showing a continuous degradation state. The intensity of the negative correlation between habitat quality and Hemeroby index was proven to be strongest in cold spot areas, hot spot areas and random areas. The spatial lag model (SLM) was better suited to spatial regression analysis due to the spatial dependence of habitat quality and disturbance factors in heterogeneous units. By analyzing the model, Hemeroby index was found to have the greatest impact on habitat quality in the studied four periods (1990, 2000, 2010 and 2018). The research results have potential guiding significance for the formulation of reasonable management policies in the TRB as well as other river basins in arid areas.

Keywords: habitat quality; biodiversity; InVEST model; spatial heterogeneity; spatial lag model; human activities; Tarim River Basin

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1 Introduction

Biodiversity is the combination of an organism, complex environment and various related ecological processes and is also the material basis for human survival (Ma et al., 1998). As human activities increase and the economy and society develop rapidly, human disturbance to ecosystems has affected the quality of biological habitats and caused a reduction in biodiversity. According to

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statistic data (2011–2020), over 1.5×10^4 species have disappeared, and the trend of biodiversity loss has not been effectively curbed; biodiversity is anticipated to decrease further in the future (Isbell et al., 2013; Terrado et al., 2016a; Dai et al., 2018). Habitat quality is the ability of an ecosystem to provide suitable living conditions for the sustainable development of individuals and populations within a certain space-time range, which reflects regional biodiversity status to a certain extent (Fellman et al., 2015; Hillard et al., 2015). Therefore, the exploration of the changes in regional habitat quality and analysis of the influencing factors of these changes are of great significance for the protection and ecological management of regional biodiversity.

Habitat quality is regarded as an important representation of regional biodiversity and ecosystem services, and the assessment, simulation and prediction of its trend and status are an effective means for studying regional ecosystem services (Wu et al., 2021). Currently, the main methods used for habitat quality assessment include the traditional biodiversity and habitat survey method (Mark et al., 2008; Miller et al., 2010), ecological index evaluation method (Maes et al., 2012; Coates et al., 2016) and ecological assessment model (Costa et al., 2010; Terrado et al., 2016a, b). Due to a lack of long-term and continuous species detection data in field biodiversity surveys, biodiversity and habitat survey methods cannot be used to evaluate the temporal and spatial dynamic changes in biodiversity (Balasooriya et al., 2008; Sun et al., 2010). For calculation, the ecological index evaluation method uses the habitat quality evaluation index system and evaluation criteria, such as the biological abundance index and vegetation coverage, which have certain defects in terms of the evaluation of dynamic changes in habitat quality and its spatial agglomeration state. With the wider application of 3S (geographic information system (GIS), global positioning system (GPS), and remote sensing (RS)) technology and mathematical models, ecological assessment models have become a powerful tool for the quantitative, visual and fine monitoring and assessment of temporal and spatial changes in habitat quality (Leh et al., 2013). Currently, the main ecological assessment models include the Habitat Suitability Index (HSI) model (Liu et al., 2006), Social Value for Ecosystem Services (SolVES) model (Sherrouse et al., 2014) and Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model (Sharp et al., 2016; Aneseyee et al., 2020). Of these, the InVEST model has the advantages of having relatively few operation parameters, easily accessing to basic data and providing quantifiable assessment results and spatial visualization; the model is widely used for studying habitat quality, particularly in large-scale basins or regions. For example, Chu et al. (2018) combined an InVEST model and Cellular Automaton (CA)-Markov method to study the evolution of landscape patterns and habitat quality in the Hubei section of the Three Gorges Reservoir Area in China. Their results demonstrated that habitat degradation and landscape pattern change are causing the continuous decline of biodiversity in the region. Aneseyee et al. (2020) used the InVEST model to analyze the temporal and spatial changes in habitat quality of different land use types in the Winike Basin (in the Omo-Gibe Basin, Southwest Ethiopia) and discussed the influence of population density, altitude, land use intensity and other factors on habitat quality.

Changes in habitat quality are a result of many factors, whereby variations in land use (landscape pattern) caused by anthropogenic factors are an important indicator that threatens habitat quality (Zheng et al., 2018; Zhang et al., 2020). In addition, the distribution of habitat quality is also affected by natural factors and other anthropogenic factors, including topography, terrain, gross domestic product (GDP) and population density. Most previous studies have focused on the impact of land use and spatial pattern change on regional habitat quality (e.g., Zheng et al., 2018). Researchers have generally directly associated land use change with habitat quality models when studying the impact of land use change on habitat quality (Chu et al., 2018; Wang et al., 2019; Wang et al., 2020). Studies have also focused on analyzing the correlation between habitat quality and natural and anthropogenic factors, including altitude, slope, GDP and intensity of land use, as a means of quantifying the impact of different disturbance factors on habitat quality (Sun et al., 2019). However, relatively few studies have been conducted on the relationship between the comprehensive indicators of human disturbance and habitat quality.

Furthermore, the heterogeneity of habitat quality has been largely ignored, and the relationship between habitat quality and human disturbance can be distorted (Zhang et al., 2018). Previous studies (Hu et al., 2015; Han et al., 2020) have demonstrated that the Getis-Ord G_i^* spatial statistical method can be used for describing and visualizing the spatial distribution of related elements and can effectively identify heterogeneous units that are related to clusters. Therefore, conducting research on the spatial heterogeneity of habitat quality and the impact of different interference factors on habitat quality can help to reveal the evolution of habitat quality when it is influenced by human activities and can scientifically guide the protection of the ecological environment and the sustainable use of land resources.

The Tarim River Basin (TRB) is located in southern Xinjiang Uygur Autonomous Region, China. It is a typical inland arid area and also an important area in terms of landscape biodiversity protection. The region has an abundance of natural resources and plays a crucial role in strategic development, but it has a fragile ecological environment (Xue et al., 2019). The geographic components of vegetation found in the TRB include desert vegetation flora. Plant species are relatively poor, mainly including *Populus euphratica*, *Tamarix chinensis*, *Glycyrrhiza uralensis* and *Phragmites communis*. The desert riparian forest with *Populus euphratica* and *Tamarix* sp. as constructive and dominant species is the main barrier for the desertification of oases (Yu et al., 2017). In recent decades, as a result of increased human activities, social activities and economic activities, the unreasonable development and utilization of water and soil resources in the TRB have caused several ecological and environmental problems (vegetation degradation, lake drought, desertification, massive loss of biodiversity and habitat degradation) (Tan et al., 2011; Ling et al., 2018). Following the implementation of the Belt and Road initiative, as the core area of the Silk Road Economic Belt (Chen et al., 2016), the habitat quality of the TRB is of great significance in terms of social and economic development, ecosystem balance and biodiversity protection. However, most existing researches on the TRB have focused on climate change, optimization of the allocation of water resources, land use change and ecological water transfer effects, whereas comparatively little research was focused on biodiversity from an ecosystem service perspective.

The main objectives of this study are as follows: (1) evaluating habitat quality between 1990 and 2018 and analyzing the temporal and spatial changes of habitat quality by determining habitat suitability and the threat to biodiversity caused by different land use types in the TRB; (2) identifying and dividing the spatial heterogeneity units of habitat quality; (3) clarifying the differences of influencing factors on habitat quality in different heterogeneous units using linear regression method; and (4) clarifying the spatial dependence of habitat quality on disturbance factors in different units using a spatial regression model. It is anticipated that the results of this study will provide a reference for the rational planning and utilization of land resources and the coordinated development of the ecological environment in the TRB.

2 Materials and methods

2.1 Study area

The TRB is located in the Tarim Basin (34°55′–43°08′N, 73°10′–94°05′E) in southern Xinjiang Uygur Autonomous Region of China and covers an area of 1.02×10^6 km^2, which includes 9 water systems and 114 rivers (Yu et al., 2016). The TRB is located at a significant distance from the ocean and is surrounded by mountains on every side. It is a closed inland hydrological region with a relatively independent water cycle and water balance (Fig. 1) (Xue et al., 2017). The Tarim River is China's largest inland river with a mainstream that is 1321 km long and does not produce any flow. Historically, the water from nine water systems in the TRB flowed into the mainstream of the Tarim River, but due to a change in the natural environment and the development of modern oasis agriculture, only three upstream rivers (Aksu River, Yarkant River and Hotan River) now have a natural hydraulic connection with it (Chen et al., 2013; Xu et al., 2013). The TRB

encompasses 5 states, 42 counties (cities), 4 production and construction companies and 55 regiments. According to statistical data, in 2018, the total population of the TRB was 13.14×10^6, the crop planting area was 2.23×10^6 hm^2, the gross national product was 411.77×10^9 CNY and the total water resources were 42.04×10^9 m^3.

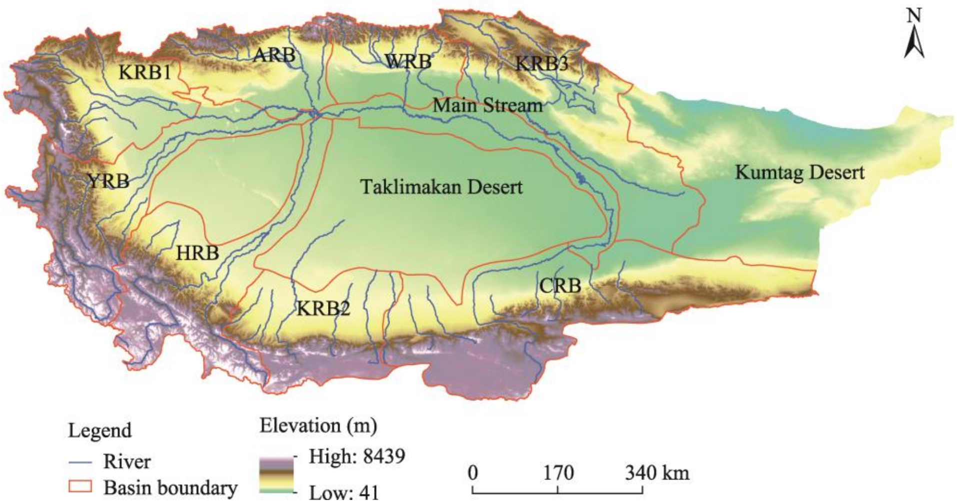


Fig. 1 Overview of the Tarim River Basin (TRB). ARB, Aksu River Basin; YRB, Yarkant River Basin; HRB, Hotan River Basin; CRB, Cherchen River Basin; WRB, Weigan-Kuche River Basin; KRB1, Kaxgar River Basin; KRB2, Keriya River Basin; KRB3, Kaidu-Konqi River Basin.

2.2 Data sources and preprocessing

In this study, we used five different data sources to calculate and analyze the temporal and spatial variations in habitat quality and spatial heterogeneity with disturbance factors. Specifically, Landsat series RS images with a resolution of 30 m×30 m from 1990, 2000, 2010 and 2018 in the TRB were chosen as the basic data sources, and the datasets were provided by the Data Centre for Resources and Environmental Sciences at the Chinese Academy of Sciences (RESDC) (http://www.resdc.cn). RS images with no clouds or few clouds between June and September were selected. Using ENVI 5.3 software, radiation correction, geometric correction, clipping and other preprocessing operations were conducted. The land use information was extracted and assigned using the human-computer interaction method, and the interpretation results were verified and corrected using GPS technology. Finally, the land use thematic map was obtained with an accuracy of 97.15% and unified classification. Land use types were categorized as cultivated land, forestland, grassland, water body, construction land and unused land using ArcGIS 10.5 software (Fig. 2) (Sun et al., 2021). The 90 m×90 m DEM (digital elevation model) data from the study area were obtained from the geospatial data cloud (http://www.gscloud.cn/). The 1 km×1 km GDP data (1990, 2000, 2010 and 2018) were obtained from the RESDC. River system data (1:1,000,000) were obtained from the RESDC. Population data (1991–2019) were obtained from the Xinjiang Statistical Yearbook (Statistics Bureau of Xinjiang Uygur Autonomous Region, 1990–2018).

2.3 Model and methods

2.3.1 Model

The InVEST model was developed by the US natural capital project team in 2007, and the habitat quality module is the one that has multiple ecosystem services for assessment (Sharp et al., 2016). The habitat quality module reflects the impact of human activities on the ecological environment; therefore, the greater the disturbance of human activities is, the greater the threat to the habitat, and the lower the quality is, the lower the biodiversity. Habitat type and threat source factors must be set when the habitat quality module is running (Zhang et al., 2011). Due to the different

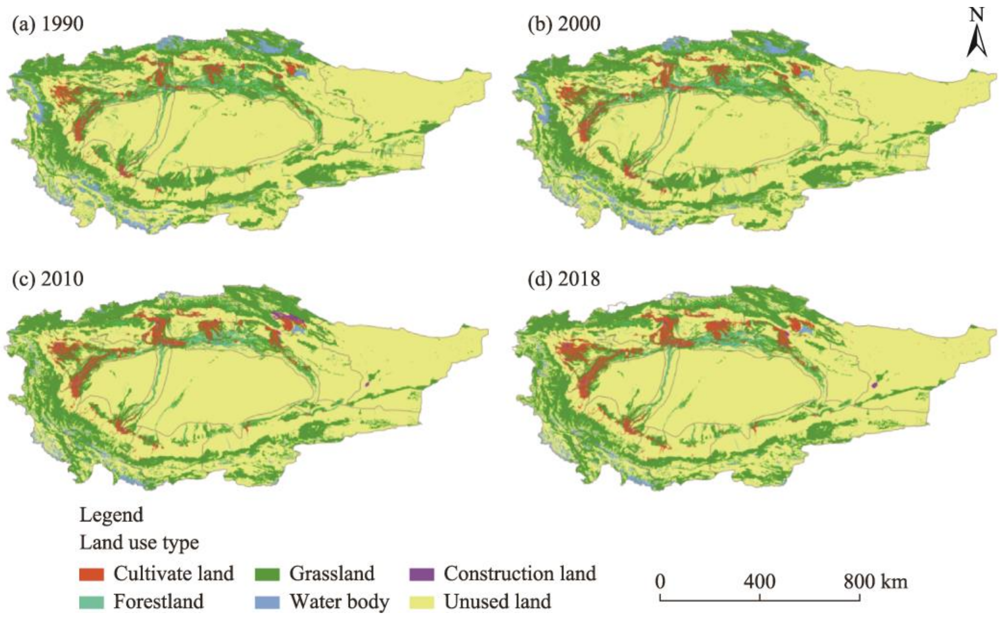


Fig. 2 Temporal and spatial distributions of land use types in the TRB in 1990 (a), 2000 (b), 2010 (c) and 2018 (d)

sensitivities of various land use types to threat source factors (Yang et al., 2018), the current situation and expert opinions of the TRB were considered in this study, and cultivated land, construction land and unused land were chosen as threat source factors. The other land use types (forestland, grassland and water body) represent different habitat types. After referring to the user manual for the InVEST model and examining previous research results (Zhang et al., 2011; Liu et al., 2020; Wang et al., 2021), we then determined the weight of threat source factors, the maximum influence distance of source factors on ecological land (Table 1) and the sensitivity of ecological land to stress factors (Table 2). The core objective of the habitat quality module is to establish the relationship between habitat types and threat source factors or to obtain the degradation degree of habitat by calculating the negative impact of threat source factors on the habitat and then determining the habitat quality based on the suitability and degradation degree of habitat. Before the model was run, all land use data and threat source factors data were rasterized using ArcGIS software. The specific calculation equations are as follows (Han et al., 2019):

$$D_{xj}=\sum_{r=1}^{r}\sum_{y=1}^{Y_r}\left(\frac{W_r}{\sum_{r=1}^{R}W_r}\right)r_y i_{rxy}\beta_y S_{jr}\,, \tag{1}$$

$$i_{rxy}=1-\left(\frac{d_{xy}}{d_{r\max}}\right)\text{(if linear)};\ i_{rxy}=\exp\left[-\left(\frac{2.99}{d_{r\max}}\right)d_{xy}\right]\ \text{(if exponential)}, \tag{2}$$

$$Q_{xj}=H_j\left[1-\left(\frac{D_{xj}^z}{D_{xj}^z-K^z}\right)\right], \tag{3}$$

where j is the habitat type; D_{xj} is the habitat degradation degree of grid x in habitat type j; r is the number of threat source factors (r=3 in this study); Y_r is the total number of grids of threat source factor r; W_r is the weight of threat source factor r; r_y is the stress value of threat source factor r to grid y; β_y is the accessibility of grid y; S_{jr} is the sensitivity of habitat type j to the threat source factors r, and the closer the value is to 1, the more sensitive it is; i_{rxy} is the stress value of grid y; d_{xy} is the distance between grid x and grid y ;d_r is the influence range of threat source factor r; Q_{xj} is the habitat quality index of grid x in habitat type j; H_j is the habitat suitability of habitat type j;

K is the semi-saturation constant, generally, half of the maximum value of D_{xj}; and z is the normalization constant, which is taken as 2.5 by default.

Table 1 Attribute table of habitat threat source factors

Threat source factor (R)	$d_{r\max}$ (km)	Weight	Spatial decay function
Cultivated land	0.35	0.60	Linear
Construction land	8.00	0.40	Exponential
Unused land	3.00	0.50	Linear

Note: $d_{r\max}$ is the maximum influence range of threat source factor r.

Table 2 Sensitivity of land use types to each threat source factor

Code	Land use type	Sensitivity			
		Habitat suitability	Cultivated land	Construction land	Unused land
10	Cultivated land	0.30	0.00	0.90	0.50
20	Forestland	1.00	0.60	0.80	0.20
30	Grassland	0.90	0.80	0.50	0.30
40	Water body	1.00	0.50	0.40	0.50
50	Construction land	0.00	0.00	0.00	0.00
60	Unused land	0.10	0.10	0.30	0.00

To compare and analyze the habitat quality changes in different years of the TRB, we used the natural break (jenk) classification in ArcGIS with four grades: low (0.00–0.25), lower (0.25–0.50), higher (0.50–0.75) and high (0.75–1.00).

2.3.2 Methods

Due to the large area of the TRB, we divided the study area into 113,916 grid units with a spatial resolution of 3 km×3 km using the "create fishing net" function module of ArcGIS 10.5 software, to analyze the spatial heterogeneity of habitat quality and its relationship with disturbance factors. Subsequent spatial autocorrelation analysis, cold-hot spot analysis, ecological disturbance degree, and the relationship between habitat quality and disturbance factors were all based on the created grids. The software used for the calculation included ArcGIS 10.5, GeoDa 1.1 and SPSS 24.0.

Hemeroby index is a comprehensive indicator of human disturbance and is determined on the basis of the comprehensive impact human activity frequency and the degree of human activities on an ecosystem (Hill et al., 2002; Chen et al., 2010). The calculation equation is as follows:

$$H = \frac{\sum_{i=1}^{m} HI_i \times S_i}{S}, \tag{4}$$

where H is the Hemeroby index of a grid cell; HI_i is the Hemeroby coefficient of the i^{th} land use type (Table 3); S_i is the i^{th} land use type in a grid cell; and S is the total number of the grid units. Based on the natural break point, we divided the Hemeroby index into three levels: low (0.0000–0.4000), medium (0.4000–0.6000) and high (0.6000–1.0000).

Table 3 Hemeroby coefficient (HI) corresponding to each land use type

	Cultivated land	Forestland	Grassland	Water body	Construction land	Unused land
HI	0.7500	0.5500	0.5000	0.3000	0.9500	0.7200

Spatial autocorrelation analysis is a method that is used for testing the potential dependence of spatial variables with a certain degree of regularity in different spatial positions based on classical statistics (Rey, 2001). As an important spatial statistical research field, the combination of global spatial autocorrelation analysis and local spatial autocorrelation analysis has been widely used in

a variety of spatial problems (Zhang et al., 2011). Spatial heterogeneity is resulted from different degrees of spatial autocorrelation (Han et al., 2020). Therefore, this study used the global spatial autocorrelation analysis method to test the heterogeneity of habitat quality within the study area. Generally, the global Moran's *I* index was used for measurement, and the calculation equation is as follows:

$$I=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}(x_i-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}\sum_{i=1}^{n}(x_i-\bar{x})^2}, \tag{5}$$

where *I* is the Moran's *I* index; *n* is the total number of grids; W_{ij} is the spatial weight matrix of raster *i* and raster *j* (if *i* is adjacent to *j*, its spatial weight is 1; otherwise, it is 0); x_i is the habitat quality values in the *i* grids; and $\bar{x}$ is the mean value of habitat quality.

When conducting spatial autocorrelation analysis, the habitat quality values for the four periods were extracted using 3 km×3 km grids. They were then processed and calculated using GeoDa software.

The method for studying the clustering distribution characteristics of local regions is known as hotspot analysis. This is a method that is used for identifying statistically significant high-value areas (hot spots) and low-value areas (cold spots) in the spatial distribution of habitat quality (Han et al., 2019). In this study, ArcGIS software was used to analyze the habitat quality of the TRB in 1990, 2000, 2010 and 2018 using the Getis-Ord G_i^* index (Getis et al., 1992). According to the calculation results of the Getis-Ord G_i^* index, we divided the study area into cold spot areas, hot spot areas and random areas. Compared with the Moran's *I* index, the Getis-Ord G_i^* index is able to determine the spatial distribution of habitat quality heterogeneity units. The calculation equation is as follows:

$$G_i^*=\frac{\sum_{j=1}^{n}W_{ij}x_j-\bar{x}\sum_{j=1}^{n}W_{ij}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n}W_{ij}^{\ 2}-\left(\sum_{j=1}^{n}W_{ij}\right)\right]^2}{n-1}}}, \tag{6}$$

where x_j is the habitat quality of raster *j*; and *S* is the standard deviation of habitat quality.

Taking the 3 km×3 km grid element as the calculation scale, the Pearson correlation coefficients of habitat quality and disturbance factors in the three habitat quality heterogeneous units (cold spot areas, hot spot areas and random areas) were calculated for 1990, 2000, 2010 and 2018 using the linear regression tool of SPSS software. The three habitat quality heterogeneity units were determined using cold-hot spot analysis.

In this study, the ordinary least square (OLS), spatial lag model (SLM) and spatial error model (SEM) proposed by Anselin (1988) were used to perform regression analysis of habitat quality and disturbance factors using GeoDa software. The calculation equation for the model is as follows (Anselin, 2005):

$$y=\rho W_1 y+\beta x+\mu+\alpha\mu=\lambda W_2+\varepsilon, \tag{7}$$

where *y* is the dependent variable, i.e., habitat quality; *ρ* is the regression coefficient of spatial lag term W_1y; W_1 and W_2 are the spatial adjacency weight matrices of the dependent variable and residual, respectively; *β* is the regression coefficient of the independent variable; *x* is the independent variable, i.e., the relevant interference factor; *μ* is a random error term; *α* is a constant; *λ* is the regression coefficient of the spatial residual term; and *ε* is a random error with a mean value of 0 and variance of δ^2.

When different parameters in Equation 7 are equal to 0, four types of spatial regression models

can be formed (Anselin, 2005). When $\rho\neq0$ and $\beta=\lambda=0$, this is a first-order spatial autoregressive model that does not take the influence of the independent variables on the dependent variables into account. Therefore, only the OLS, SEM and SLM models were considered for use in this study. When $\rho=0$ and $\lambda=0$, the OLS model is defined, and the observed values of the dependent and independent variables in space are unaffected by spatial differences. When $\rho\neq0$ and $\lambda=0$, the SLM model is defined, and there is a spatial correlation between the dependent variables in space, with the observed values of the dependent variables being related to the corresponding independent variables and the dependent variables in the adjacent areas. When $\rho=0$ and $\lambda\neq0$, the SEM model is defined. In this case, there is no spatial correlation between the dependent variables in space, and only the independent variables with spatial correlation are considered. In addition, the observation values of the dependent variables in space are related to the corresponding independent variables as well as the independent variables and dependent variables in adjacent areas.

3 Results

3.1 Temporal and spatial variations of habitat quality in the TRB

Based on the dynamic change in land use types in the TRB between 1990 and 2018, we evaluated habitat quality of four periods (1990, 2000, 2010 and 2018) using the habitat quality module of the InVEST model. In ArcGIS, habitat quality values were divided into four grades: 0.0000–0.2500, 0.2500–0.5000, 0.5000–0.7500 and 0.7500–1.0000. The smaller the value was, the worse the habitat quality. Figure 3 shows that the overall level of habitat quality for the entire TRB was poor (in the range of 0.2500–0.5000), and the average habitat quality continued to decrease from 0.3000 in 1990 to 0.2700 in 2018, which indicated that habitat quality in the study area was in a state of degradation. Between 1990 and 2018, habitat quality in each sub-basin exhibited different degrees of degradation (with the exception of the Hotan River Basin (HRB)). The spatial distribution of habitat quality demonstrated that there were differences in habitat quality between sub-basins in the study area (Tables 4 and 5). Habitat quality of the northern sub-basins (Kaxgar River Basin (KRB1), Aksu River Basin (ARB), Weigan River Basin (WRB) and Kaidu-Konqi River Basin (KRB3) was higher than that of the southern sub-basins (HRB, Keriya River Basin (KRB2), and Cherchen River Basin (CRB)), and habitat quality of high-altitude areas (gradient 3 (3000–4500 m) and gradient 4 (4500–8439 m); Table 5) was higher

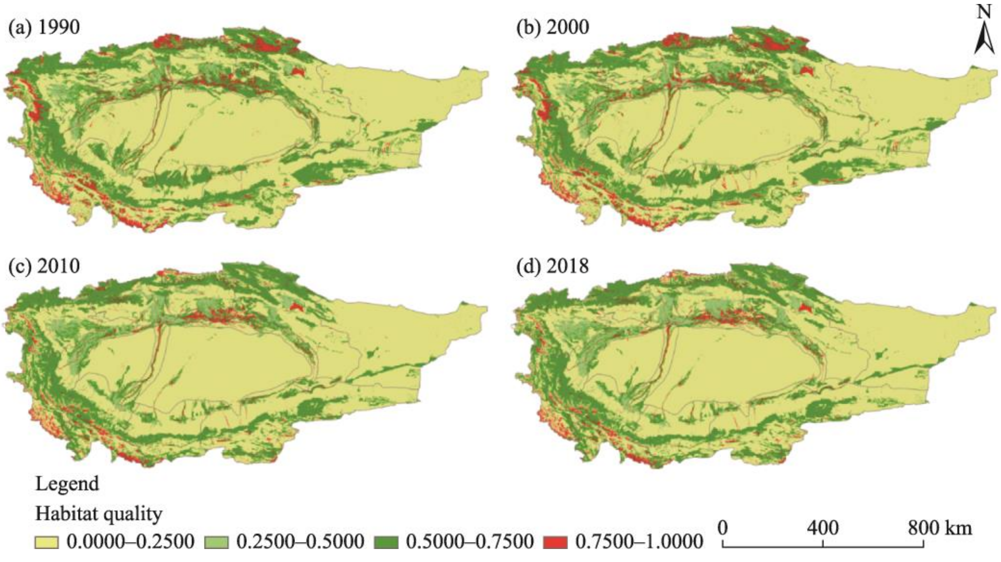


Fig. 3 Spatial distribution of habitat quality in the TRB in 1990 (a), 2000 (b), 2010 (c) and 2018 (d)

Table 4 Changes in habitat quality in the sub-basins of the TRB from 1990 to 2018

Sub-basin	Habitat quality				
	1990	2000	2010	2018	Value change (1990–2018)
ARB	0.4476	0.4362	0.4292	0.4146	–0.0330
KRB1	0.4530	0.4552	0.4156	0.4097	–0.0433
YRB	0.4410	0.4391	0.4282	0.4257	–0.0153
HRB	0.3605	0.3521	0.3729	0.3724	0.0119
KRB2	0.3597	0.3533	0.2894	0.2896	–0.0701
CRB	0.2878	0.2895	0.2715	0.2713	–0.0165
KRB3	0.3649	0.3634	0.3327	0.3327	–0.0322
WRB	0.4268	0.4290	0.3649	0.3584	–0.0684
Mainstream	0.4968	0.4828	0.4471	0.4459	–0.0509
Taklimakan Desert	0.1409	0.1365	0.1203	0.1205	–0.0204
Kumtag Desert	0.1384	0.1371	0.1351	0.1342	–0.0042
TRB	0.2981	0.2950	0.2766	0.2746	–0.0235

Note: TRB, Tarim River Basin; ARB, Aksu River Basin; KRB1, Kaxgar River Basin; YRB, Yarkant River Basin; HRB, Hotan River Basin; KRB2, Keriya River Basin; CRB, Cherchen River Basin; KRB3, Kaidu-Konqi River Basin; WRB, Weigan-Kuche River Basin.

Table 5 Habitat quality changes in the TRB at different altitudinal gradients from 1990 to 2018

Altitudinal gradient	Habitat quality				
	1990	2000	2010	2015	Value change (1990–2018)
Gradient 1	0.2266	0.2222	0.1991	0.1980	–0.0330
Gradient 2	0.3377	0.3381	0.3311	0.3317	–0.0433
Gradient 3	0.5238	0.5229	0.4802	0.4743	–0.0204
Gradient 4	0.3727	0.3697	0.3795	0.3775	–0.0042
TRB	0.2981	0.2950	0.2766	0.2746	–0.0235

Note: Gradient 1, 41–1500 m; Gradient 2, 1500–3000 m; Gradient 3, 3000–4500 m; Gradient 4, 4500–8439 m. The division of elevation gradient 1 is based on the fact that most hydrological stations at the outflow of the mountains are 1500 m above sea level, and the outflow hydrological station is divided into mountainous and plain areas. In addition, the classification of elevation gradient 4 is based on the existence of permanent snow and glaciers in the mountainous areas of above 4500 m. Elevation gradient 2 and elevation gradient 3 are divided on the basis of the isometric interval.

than that of low-altitude areas (gradient 1 (41–1500 m) and gradient 2 (1500–3000 m); Table 5). The spatial differences of habitat quality between 1990 and 2018 were obvious. With the exceptions of the Taklimakan Desert and Kumtag Desert, the lowest habitat quality was found to be mostly concentrated in oasis areas with frequent human activities, while the highest habitat quality was generally concentrated in mountains and water bodies.

3.2 Heterogeneity of habitat quality in the TRB

Based on the spatial distribution of habitat quality of the TRB in the fourth periods (1990, 2000, 2010 and 2018) and according to the calculation process of Equation 4, we tested the spatial autocorrelation of habitat quality using GeoDa software. The results shown in Figure 4 demonstrated that when $P<0.05$, the global Moran's I index values of habitat quality during the four periods from 1990 to 2018 were 0.8465, 0.8437, 0.8429 and 0.8395, respectively, thereby confirming the existence of spatial autocorrelation of habitat quality, i.e., signs of heterogeneity. Generally, the global autocorrelation index displayed a continuous weakening trend between 1990 and 2018, but the decreasing range was very small, which indicated that the spatial heterogeneity had a weak decreasing trend.

We divided the spatial heterogeneity units of habitat quality in the TRB into three types according to Equation 5: cold spot areas, hot spot areas and random areas. Habitat quality of the TRB from 1990 to 2018 was then analyzed using the Getis-Ord G_i^* index in ArcGIS; the results

of which are shown in Figure 5. According to ArcGIS statistics, cold spot areas accounted for 42.03%, 41.67%, 54.27% and 63.97% of the study area in 1990, 2000, 2010 and 2018, respectively; hot spot areas accounted for 26.07%, 25.79%, 22.89% and 20.25%, respectively; and random areas accounted for 31.90%, 32.54%, 22.84% and 15.78%, respectively. Spatially, the distribution pattern of cold spot areas and hot spot areas of habitat quality was "cold inside and hot outside, cold in the east and hot in the west" and displayed obvious heterogeneity. Cold spot areas were mainly concentrated in the Taklimakan Desert and Kumtag Desert, and the KRB and CRB had more cold spot areas than the other sub-basins. The land use types in cold spot areas were mainly alpine desert, bare rock land or grassland with low vegetation coverage; therefore, habitat quality was low, with average habitat quality of 0.1240. The hot spots were mainly located in oasis areas, mountain areas and mainstream of the Tarim River (ecological protection area). Due to the relatively high vegetation coverage in these areas, there was generally a high habitat quality (average habitat quality of 0.6594). Regarding time change, the range of cold spot areas exhibited a continuously increasing trend from 1990 to 2018, whereas hot spots in mountainous areas showed an increasing trend.

3.3 Analysis of the change in Hemeroby index

Based on the spatial distribution of land use types in the Tarim River Basin between 1990 and 2018, we calculated the spatial distribution of Hemeroby index in the TRB using Equation 4; results are shown in Figure 6. According to the statistics (Table 6), Hemeroby index of the TRB during the four periods (1990, 2000, 2010 and 2018) were at high levels: 0.6459, 0.6472, 0.6586 and 0.6608, respectively. This showed a general upward trend, which indicated that the impact of

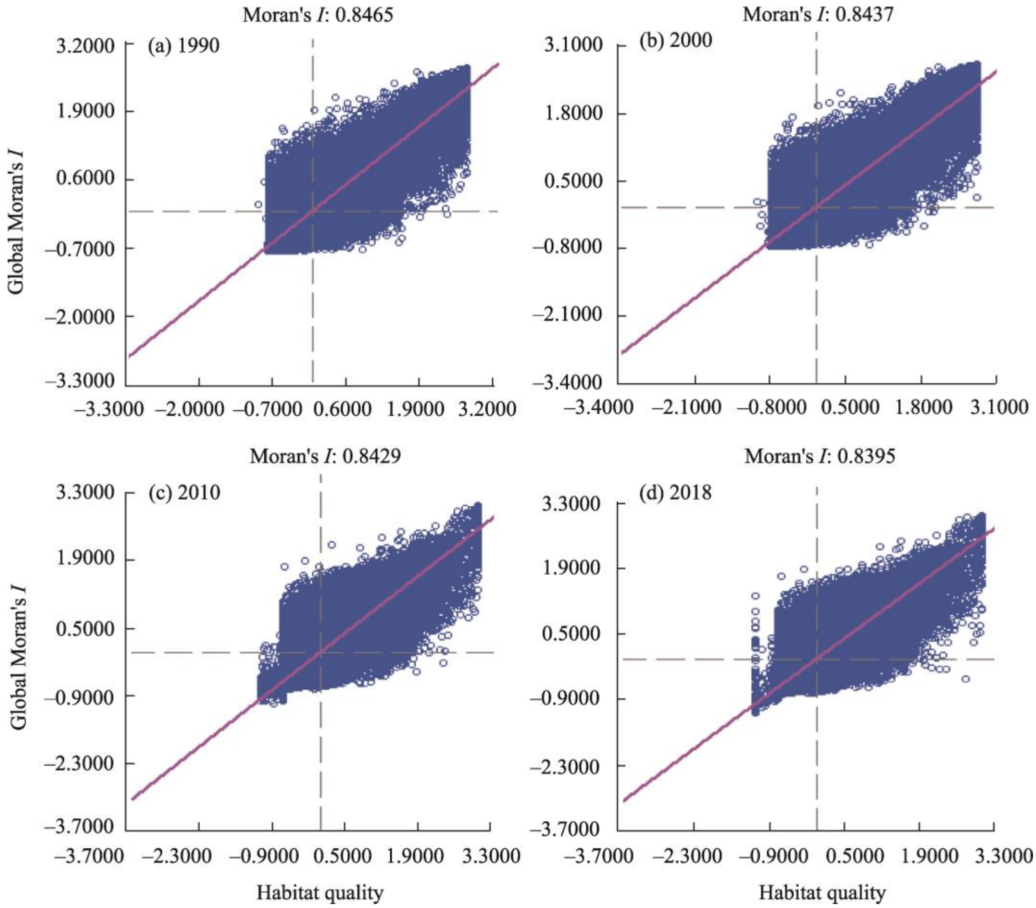


Fig. 4 Global Moran's I index statistics of habitat quality in the TRB in 1990 (a), 2000 (b), 2010 (c) and 2018 (d)

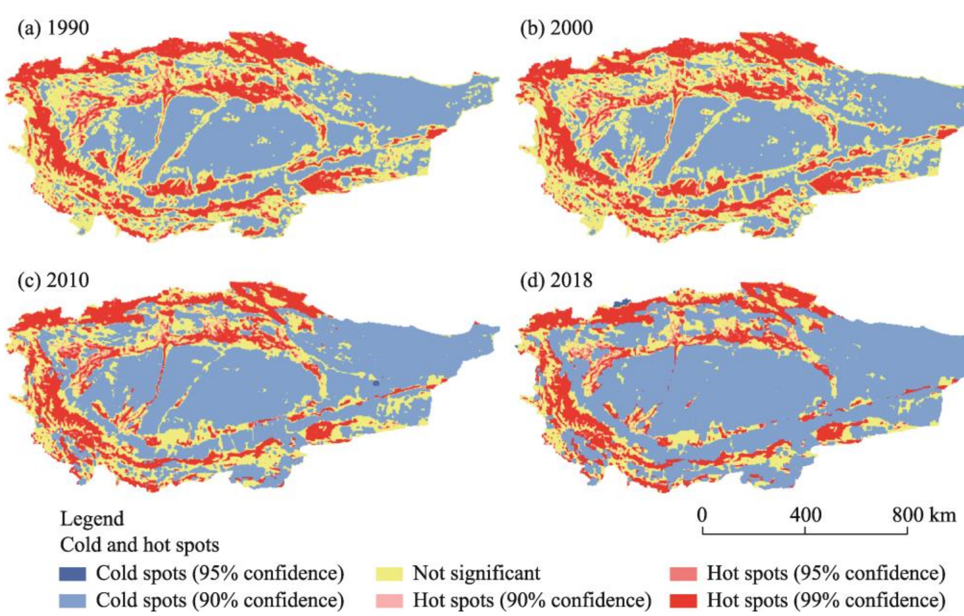


Fig. 5 Spatial distribution of cold spots and hot spots of habitat quality in the TRB in 1990 (a), 2000 (b), 2010 (c) and 2018 (d)

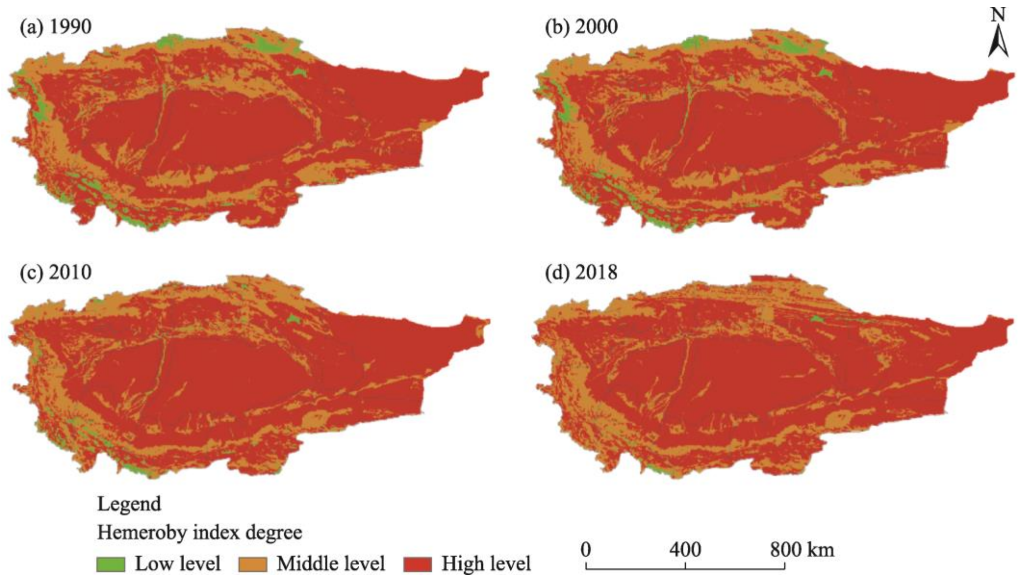


Fig. 6 Distribution of Hemeroby index degree levels in the TRB in 1990 (a), 2000 (b), 2010 (c) and 2018 (d)

Table 6 Hemeroby index at different altitudinal gradients in 1990, 2000, 2010 and 2018

Altitudinal gradient	Hemeroby index			
	1990	2000	2010	2018
Gradient 1	0.6791	0.6810	0.6906	0.6905
Gradient 2	0.6337	0.6331	0.6439	0.6486
Gradient 3	0.5519	0.5522	0.5772	0.5820
Gradient 4	0.6905	0.6486	0.5820	0.5950
TRB	0.6459	0.6472	0.6586	0.6608

human disturbance on the ecological environment was intensifying between 1990 and 2018. In terms of spatial distribution, Hemeroby index was similar to the distribution pattern of cold spots and hot spots, displaying a pattern of "high inside and low outside, high in the east and low in the west". In addition to the desert areas, Hemeroby index with high level was mainly distributed in low-altitude areas (gradient 1 and gradient 2). These areas were mainly oases with frequent human activities; therefore, Hemeroby index was high. Hemeroby index with middle level was mainly distributed in the mountainous areas (gradient 3) with less human activities, more precipitation and higher vegetation coverage. There were few areas with low level of Hemeroby index, and they were mainly distributed around lakes and other water bodies. In terms of time scale, the areas of low- and middle-level ecological interference continued to decrease (with the exception of desert areas) between 1990 and 2018, and the ecological interference degree of the same altitude area displayed an increasing trend, showing that the impact of human activities on the ecological environment was intensifying.

3.4 Linear relationship between habitat quality and disturbance factors

3.4.1 Selection of disturbance factors

Results in Section 3.3 showed that from 1990 to 2018, Hemeroby index in the TRB displayed an increasing trend, and habitat quality was in a state of degradation. As the premise and foundation of ecosystem service functions, habitat quality has a number of disturbance factors (Fellman et al., 2015; Hillard et al., 2015; Han et al., 2020). Hemeroby index is a comprehensive indicator of human disturbance and reflects the disturbance degree of landscape type (or land use type) change on an ecological environment. Therefore, during the analysis of habitat quality and disturbance factors, it is also necessary to consider other natural and human factors, in addition to the availability of data. Relevant studies (Sun et al., 2019; Aneseyee et al., 2020) have shown that population density, socioeconomic factors, topography and geomorphology have impacts on the distribution of habitat quality. The water system structure of the TRB is separate, and "water is oasis, no water is desert" is the typical characteristic of the basin. Water plays a crucial role in the ecological environment of the basin (particularly the mainstream of the Tarim River). Based on the above characteristics, this study chose Hemeroby index, population density, GDP, altitude and distance from water source (DWS) as the main disturbance factors. The above five variables were diagnosed using collinearity (Fig. 7), and the results demonstrated that the variance inflation factor (VIF) values for each disturbance factor in different years were less than 5.0, which indicated that there was no collinearity between the factors.

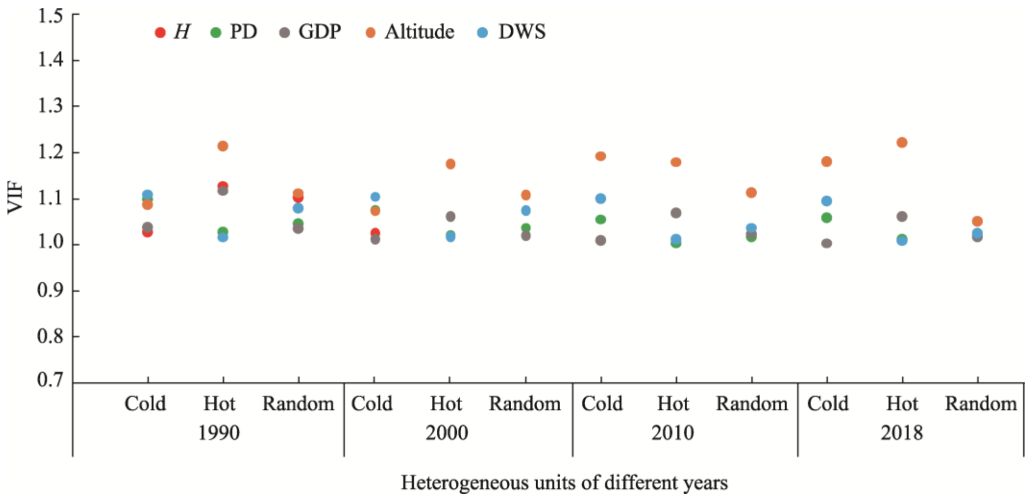


Fig. 7 Results of variance inflation factor (VIF) in collinearity diagnostics for the main disturbance factors. Cold, cold spots; Hot, hot spots; Random, random areas. *H*, Hemeroby index; PD, population density; GDP, gross domestic product; DWS, distance from water source.

3.4.2 Linear relationship between habitat quality and disturbance factors

The correlation between habitat quality and disturbance factors in the three heterogeneous units can be seen in Figure 8. Different disturbance factors had different correlations with habitat quality in different years. A significant and negative linear relationship was found between habitat quality and Hemeroby index in the three heterogeneous units (P<0.01), and the correlation coefficient was largest, which indicated that Hemeroby index was the key disturbance factor that caused the degradation of habitat quality. Habitat quality showed a positive linear relationship with population density and GDP in cold spot areas and random areas and a significant and negative linear relationship in hot spot areas, which indicated that population density and GDP facilitated habitat quality degradation in hot spot areas but not in cold spot areas and random areas. The reason for this difference is that hot spot areas were the main population gathering regions with frequent human activities, which can directly or indirectly affect the habitat.

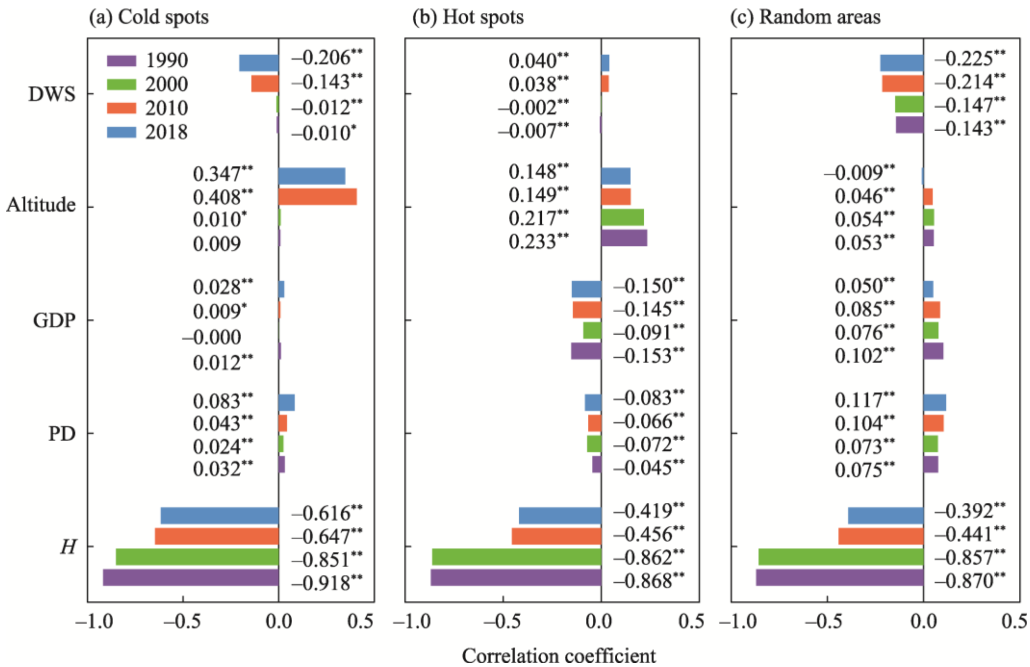


Fig. 8 Relationship between habitat quality and disturbance factors in cold spot areas, hot spot areas and random areas. *, statistically significant at the 5% level; **, statistically significant at the 1% level.

There was a significant and positive correlation between habitat quality and altitude, indicating that habitat quality improved with increasing altitude, but the correlation coefficient in hot spot areas decreased between 1990 and 2018. There was a significant and negative linear relationship of between habitat quality and DWS in cold spot areas and random areas, and the correlation coefficient increased (from 1990 to 2018), indicating that habitat quality worsened in these areas farther away from water sources. Further, there was a significant and negative linear relationship between habitat quality and DWS in the period of 1990–2000 and then a significant and positive correlation in the period of 2010–2018, which indicated that the ecological environment of the TRB improved following the implementation of ecological management projects (particularly the ecological water conveyance project) after 2000.

3.4.3 Spatial relationship between habitat quality and disturbance factors

The spatial relationship between habitat quality and disturbance factors (Hemeroby index, population density, GDP, altitude and DWS) of the three heterogeneous units (cold spot areas, hot spot areas and random areas) in the TRB between 1990 and 2018 was statistically tested and compared using the regression modeling tool of the GeoDa software to enable the selection of the optimal spatial regression model. The evaluation indices of the spatial regression model included

correlation coefficient (R^2), log (Likelihood) (log$L$), Akaike information criterion (AIC) and Schwartz criterion (SC). The range of R^2 values was 0.0000–1.0000, and the closer the R^2 values were to 1.0000, the better the regression effect of the spatial regression model. In addition, the larger the log$L$ value and the smaller the AIC and SC values were, the better the regression effect of the model. According to the OLS, it was necessary to judge the significance of the Lagrange multiplier (LM) and Robust lagrange multiplier (RLM). The larger the values of the two were, the better the regression effect of the spatial regression model. Table 7 shows that the global Moran's *I* (error) values of the three heterogeneous units between 1990 and 2018 were significant at P<0.01 level, which indicated that there was a spatial dependence in all spatial regressions. Furthermore, LM (lag) and LM (error) all passed the significance test of 1%. Therefore, SEM or SLM regression was better suited to the study of habitat quality and disturbance factors than the OLS regression. The regression model with the best fitting effect was chosen following a comparison between the LM and RLM values of the three heterogeneous units for each year. By examining the advantages and disadvantages, the SLM was deemed to be more suitable for the spatial regression analysis.

Table 7 Comparison of statistical test goodness of the spatial regression models in different heterogeneous units in 1990, 2000, 2010 and 2018

Heterogeneous unit	Statistic	1990	2000	2010	2018
Cold spot areas	R^2	0.9343	0.9259	0.5232	0.4690
	log$L$	198,929.0	198,940.0	59,972.3	50,485.7
	AIC	–397,845.0	–397,868.0	–119,933.0	–100,959.0
	SC	–397,791.0	–397,813.0	–119,877.0	–100,904.0
	Moran's *I* (error)	68.9**	72.0**	347.3**	388.0**
	LM (lag)	556.4**	415.0**	84,837.9**	116,775.9**
	RLM (lag)	1.2	51.6**	94.3**	1128.1**
	LM (error)	4736.6**	5182.9**	120,561.3**	150,482.0**
	RLM (error)	4181.4**	4819.5**	35,817.7**	34,834.2**
Hot spot areas	R^2	0.8447	0.8367	0.3661	0.3367
	log$L$	47,430.2	45,911.6	17,201.2	15,911.7
	AIC	–94,848.3	–91,811.2	–34,390.4	–31,811.3
	SC	–94,796.2	–91,759.1	–34,338.4	–31,759.4
	Moran's *I* (error)	245.0**	242.3**	192.2**	188.8**
	LM (lag)	3771.4**	4116.7**	20,683.1**	21,503.1**
	RLM (lag)	3638.0**	3501.3**	1402.6**	778.3**
	LM (error)	59,975.4**	58,627.1**	36,908.3**	35,592.3**
	RLM (error)	59,842.0**	58,011.8**	17,627.7**	14,867.5**
Random areas	R^2	0.8928	0.8826	0.4390	0.3832
	log$L$	73,152.8	72,003.3	30,106.2	13,218.4
	AIC	–146,294.0	–143,995.0	–40,200.4	–26,424.8
	SC	–146,239.0	–143,940.0	–40,147.8	–26,374.4
	Moran's *I* (error)	312.3**	319.7**	220.1**	175.3**
	LM (lag)	23,710.9**	26,155.5**	30,901.5**	20,351.3**
	RLM (lag)	635.5**	615.1**	219.4**	148.4**
	LM (error)	97,456.1**	102,120.4**	48,391.0**	30,678.2**
	RLM (error)	74,380.7**	76,580.0**	17,709.0**	10,475.3**

Note: R^2, Correlation coefficient; log$L$, log(Likelihood); AIC, Akake information criterion; SC, Schwartz criterion; LM, Lagrange multiplier; RLM, Robust lagrange multiplier; **, statistically significant at the 1% level.

According to the spatial regression coefficient (Table 8), the regression coefficients of habitat quality with Hemeroby index, altitude and DWS in each heterogeneous unit between 1990 and 2018 was negative (P<0.01), which indicated that there was a significant negative correlation

between habitat quality and these disturbance factors. However, the correlation was different in the three heterogeneous units. The negative correlation coefficient between habitat quality and Hemeroby index was the largest, which indicated that Hemeroby index had the greatest impact on habitat quality. The impact of Hemeroby index on habitat quality in cold spot areas and random areas was greater than that in hot spot areas. There was a significant and positive correlation between habitat quality and GDP (P<0.01), and the correlation was greater in hot spot areas. There was a positive correlation between habitat quality and population density in cold spot areas and random areas, but there was a negative correlation between them in hot spot areas, indicating that there was a greater likelihood that human aggregation in hot spot areas will affect habitat quality. Generally, the effects of habitat quality in different heterogeneous units on the spatial dependence of disturbance factors were different.

Table 8 Spatial regression results of habitat quality with disturbance factors in different heterogeneous units in 1990, 2000, 2010 and 2018 based on the spatial error model

Heterogeneous unit	Variable	1990	2000	2010	2018
Cold spot areas	Constant	1.8829**	1.8855**	1.2565**	1.1626**
	H	–2.4739**	–2.4775**	–1.5976**	–1.4406**
	PD	0.0013	0.0051**	0.0014**	0.0043**
	GDP	0.0068**	0.0349**	0.0571**	0.0158**
	Altitude	–0.0068**	–0.0069**	–0.0016**	–0.0017**
	DWS	–0.0073**	–0.0075**	–0.0019**	–0.0041**
Hot spot areas	Constant	1.6167**	1.6592**	1.3339**	1.3222**
	H	–1.901**	–1.8900**	–1.2942**	–1.2416**
	PD	–0.0028**	–0.0086	–0.0045**	–0.0057**
	GDP	0.0169**	0.0580**	0.0876**	0.0303**
	Altitude	–0.0025**	–0.0026**	–0.0017**	–0.0021**
	DWS	–0.0019**	–0.0021**	–0.0034**	–0.0043**
Random areas	Constant	1.8317**	1.8260**	1.2711**	1.2653**
	H	–2.3133**	–2.2993**	–1.4637**	–1.3628**
	PD	0.0117**	0.0097**	0.0048**	0.0071**
	GDP	0.0146**	0.0652**	0.0935**	0.0103**
	Altitude	–0.0016**	–0.0016**	–0.0047**	–0.0016**
	DWS	–0.0023**	–0.0025**	–0.0074**	–0.0010**

Note: *H*, Hemeroby index; PD, population density; GDP, gross domestic product; DWS, distance from water source. **, statistically significant at the 1% level.

4 Discussion

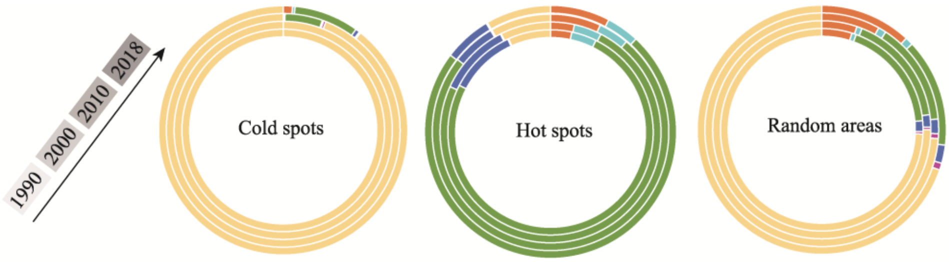
4.1 Spatial and temporal characteristics of habitat quality heterogeneity

This study discovered that habitat quality of the TRB displayed a continuous degradation trend between 1990 and 2018, and the sub-basins (with the exception of the HRB) also showed different degrees of degradation. There were differences in habitat quality in different sub-basins and at different altitudes. Habitat quality was also generally better in the northern region of the study area than in the southern region and in high-altitude areas than in low-altitude areas. This could be because there was a greater vegetation coverage in the northern region than in the southern region and the frequency of human activities in high-altitude areas was lower. These results were consistent with those obtained by Liu et al. (2020) on the spatial and temporal changes in habitat quality in Xinjiang of China: the overall habitat quality in Xinjiang displayed a degradation trend, and the areas with high values of habitat quality were mainly located at the

edge of mountains and basins (Liu et al., 2020). At the same time, the results of our study were also similar to those obtained by research on the landscape biodiversity of the YRB in the TRB by Huang et al. (2020): areas with low values of habitat quality were mainly distributed in regions with a poor natural environment and areas with high values of habitat quality were mainly distributed in natural forests and grassland reserves (Huang et al., 2020). Our study also confirmed that there was a significant spatial heterogeneity in habitat quality of the TRB, and the study area can be divided into three heterogeneous units in terms of habitat quality: cold spot areas, hot spot areas and random areas (Fig. 5). In the three heterogeneous units, cold spot areas were mainly concentrated in low-altitude areas, which were the main regions of human activities, in addition to the two large deserts (Taklamakan Desert and Kumtag Desert). Hot spot areas were mainly distributed in high-altitude mountainous regions or ecological protection regions, as these areas had relatively high vegetation coverage.

4.2 Effects of different disturbance factors on habitat quality

Hemeroby index quantifies the disturbance degree of human activities on an ecosystem by considering the degree of disturbed landscape or habitat in relation to the natural landscape or habitat (Anselin, 1988; Chen et al., 2010). Cultivated land, construction land and unused land were threat source factors to habitat quality. Their changes significantly impacted habitat quality. Figure 9 showed that the proportion of threat source factors in the three heterogeneous units was largest (with the exception of natural vegetation), which explained the significant and negative correlation between habitat quality and Hemeroby index. However, the negative correlation between habitat quality and Hemeroby index has decreased since 2000, potentially because the comprehensive management policy of the TRB has effectively restrained the deterioration of the ecological environment in the region. Among other disturbance factors, population density and GDP exhibited opposite correlations in cold spot areas, random areas and hot spot areas. Combined with the gradual deterioration of habitat quality in the oasis areas in Figure 3 and the increasing proportion of cultivated land in Figure 9, this showed that human activities had a negative impact on habitat quality of hot spot areas.



	Area percentage (%)				Area percentage (%)				Area percentage (%)			
Cultivate land	0.0000	0.0000	0.1698	1.1979	3.3306	3.4756	6.9095	7.6282	4.8131	5.2312	8.1141	11.8638
Forestland	0.0021	0.0042	0.0857	0.3246	3.9638	4.0679	4.1679	4.1916	0.7045	0.7878	1.1037	1.0324
Grasland	0.0104	0.0042	5.1956	8.4059	75.2913	74.2545	74.5015	73.5876	18.0500	16.7512	14.3055	14.0792
Construction land	0.0000	0.0000	0.1828	0.5501	0.0000	10.6822	5.9701	6.0878	1.7172	1.8319	2.0189	2.3605
Water body	0.0021	0.0021	0.3284	0.1884	0.1381	0.1328	0.1725	0.1605	0.3825	0.3804	0.6653	0.8873
Unused land	99.9854	99.9895	94.0377	89.3331	6.7017	7.3870	8.2784	8.3442	74.3327	75.0175	73.7925	69.7768

Fig. 9 Area percentages of land use types in the three heterogeneous units. The arrow direction and years indicated that the circles from outside to inside were 1990, 2000, 2010 and 2018, respectively. Values in the table represented the area percentages of land use types. The colors for area percentages of land use types were consistent with those of years.

4.3 Limitations of the InVEST model

The InVEST model compensates for the shortcomings of traditional ecosystem service assessment methods and provides an effective way for assessing ecosystem services. In recent

years, as a function module of the InVEST model, habitat quality assessment has been widely conducted (Sharp et al., 2016; Babbar et al., 2021). However, the model has some shortcomings when assessing habitat quality. For example, it obtains the habitat quality in a study area by accumulating the influence of threat source factors on habitat quality, but the simple accumulation of threat source factors is not exactly equal to the comprehensive impact of these stress factors. Therefore, the model requires further improvement in terms of the usage process. The parameters of threat source factors and habitat sensitivity are subjective and require further study in the future.

5 Conclusions

Through an analysis of the spatial and temporal changes in habitat quality in the TRB between 1990 and 2018, this study discussed the spatial heterogeneity of habitat quality and quantified its relationship with interference factors, thereby providing a new comprehensive method for the quantification of the impact of threat source factors on habitat quality. The main conclusions are as follows.

Temporally, the overall level of habitat quality in the TRB was poor and in a state of continuous degradation. Spatially, habitat quality in the northern region was greater than that in the southern region and greater in high-altitude areas than in low-altitude areas. The results showed that habitat quality exhibited spatial heterogeneity in the TRB, represented by cold spot areas, hot spot areas and random areas. There was a significant negative linear relationship between habitat quality and Hemeroby index in the three heterogeneous units, and the correlation coefficient was greater than the correlation coefficients of habitat quality with population density, GDP, altitude and DWS. There was a spatial dependence between habitat quality and disturbance factors in the three heterogeneous units. During the four periods (1990, 2000, 2010 and 2018), habitat quality in each heterogeneous unit had a significant and negative correlation with Hemeroby index, altitude and DWS, but the correlation coefficient with Hemeroby index was the largest, which indicated that Hemeroby index had the greatest impact on habitat quality.

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